State of Charge Management for Plug in Hybrid Electric Vehicles with Uncertain Distance to Recharge

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***Abstract*—The state of charge management of plug in hybrid vehicles differs from their non-plug in counterparts through the utilisation of a charge depleting mode of operation. Several studies have shown that a blended mode of charge depletion holds fuel economy advantages over a charge depletion and charge sustaining combination, however these approaches assume knowledge of the total journey distance. Here, this assumption is relaxed and the state of charge trajectory recalculated online using a weaker assumption that only a probability distribution accumulated over past trips is available. The benefits relative to other potential strategies are assessed in terms of relative fuel consumption and tailpipe CO_2 emissions.**

I. Introduction

With up-front costs and range anxiety often cited as detractors for fully electric vehicles, plug-in hybrids potentially offer an alternative for consumers and fleets seeking lower running costs and tailpipe emissions. Many of the current plug in hybrid electric vehicle (PHEV) architectures utilise a parallel powertrain arrangement, and as with parallel hybrid powertrains, the fuel economy of a plug-in variant is affected by how the battery and engine are scheduled.

While initial work on PHEVs considered using a charge depletion-charge sustaining strategy, where the vehicle was run in EV-mode until some state of charge limit was reached, the benefits of utilising a blended mode of operation were noted in [1], [2]. Various heuristic methods have been suggested to capitalise on the extra degree of freedom offered by plug-in capability [3], [4].

To ensure optimality of blended mode operation however, both the distance between recharges and the driving conditions must be known a priori. Stochastic dynamic programming using a set of possible drive cycles has been suggested as one way of coping with unknown drive cycle information [5], but requires potentially large computation time and the existence of statistically relevant datasets.

Equivalent charge maintenance strategies (ECMS) using Pontryagin's Minimum Principle have been analytically shown to be fuel optimal for parallel hybrid powertrains (see e.g. [6]) when state constraints are not active. ECMS was first demonstrated on plug-in hybrids using large datasets of drive-cycles in [7]. The exact implementation of ECMS strategies requires the drive cycle to be known in advance, so that the fuel-optimal Lagrange parameter (denoting the equivalent cost ratio of fuel and electricity to ensure the state of charge endpoint is met) may be calculated.

The fuel performance of ECMS strategies has previously been shown to be reasonably approximated by adapting the Lagrange multiplier using feedback on the state of charge [8]. To update in this manner requires a reference state of charge trajectory, which ideally should estimate the possible future regeneration capability of the battery. This latter point includes consideration of vehicle deceleration due to traffic or terrain, with some small advantage in altitude profile observed in [9]. Meanwhile, [10] demonstrate an approach for developing a state of charge reference for use with charge sustaining operation of parallel hybrids, although extending to PHEVs still requires knowledge of the trip duration - a common assumption in PHEV energy management.

In this work the assumption of known trip duration is partially relaxed. It is assumed that a probability density function of distance between recharges is available, and this is used in to develop a state of charge reference trajectory. Tracking of the reference trajectory using an adaptive ECMS approach on a comprehensive simulation platform using a prototype PHEV is undertaken to establish the benefits of the proposed approach.

II. Simulation background

The vehicle used is a prototype developed at IFP Energies Nouvelles and based on the platform of a Renault Kangoo van. It is a parallel hybrid with potential plug-in (PHEV) functionality. The vehicle is equipped with a PSA ET3J4 engine which is a naturally aspirated, 4-cylinder, 1.346 L gasoline engine producing maximum torque of 120 Nm and maximum power of 65 kW.

A five speed robotized gear box mediates between the engine and the differential. As well as the 37.7kW, 36Nm Parvex electric motor having maximum speed of 20000 rev/min, there

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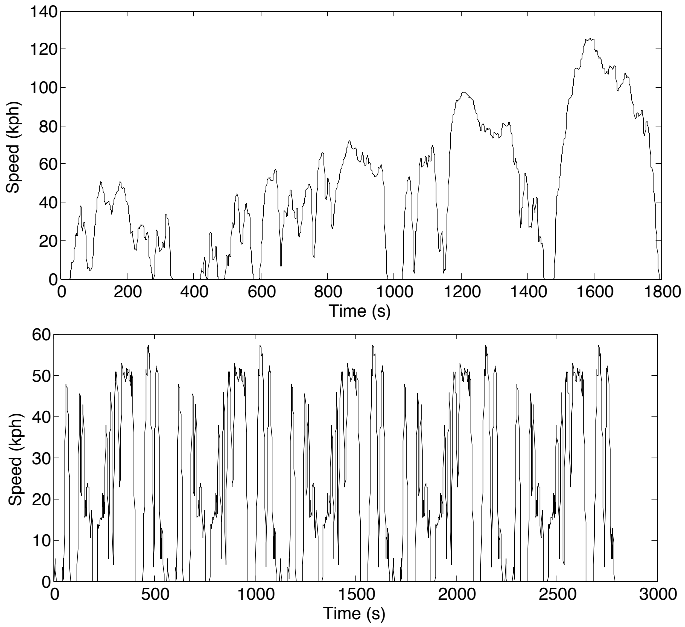

Fig. 1. Drive cycles used. (Top) WLTP cycle (bottom) a repeated modem-Hyzem base urban cycle

is also a Starter-Generator (SSG) available in the powertrain. The SSG in the present architecture is only used to start up the engine and not to supply power to the wheels and it is powered separately through a lead acid battery. The energy storage system has a Li-Ion cell based battery of capacity 39Ah and voltage between 145 V to 216 V.

The vehicle's electrical and fuel consumption was estimated over different driving conditions using the Hybrid Opimization Tool (HOT), an in-house software developed within IFP Energies Nouvelles that contains detailed sub-models derived from experimental data, and used for optimizing energy management in hybrid vehicle using principles of optimal control. This software, has previously been used in the development and optimisation of many hybrid powertrain controllers, see for example [11]–[13].

As the focus of PHEV usage is in urban environments, two urban cycles were used as the basis of the simulated drive cycles. The World Harmonized Light Duty Test Procedure (WLTP) is mooted to become the regulatory cycle in several countries [14], while several repetitions of a modem-Hyzem urban base cycle [15] were also used. Both cycles are illustrated in Figure II. The WLTP cycle lasts 1800 seconds and covers 23.195km, while the iterations of the modem-Hyzem urban cycle lasts 2800 seconds and covers 17.348km.

These were combined as discussed in the relevant latter sections of this manuscript to produce cycles of longer durations.

III. PHEV POWERTRAIN CONTROLLER

The powertrain controller used here is an optimal approach based on initial work in [6]. Although the focus of this work is on the generation of the battery state of charge reference, the map-based optimal powertrain controller is summarised here given it's relevance. Quasi-steady maps of fuel and charge consumption, m_f and q respectively, are used in a general Hamiltonian-based controller design for a hybrid powertrain with control inputs u:

$$M_f = \int f(u,t)dt \tag{1}$$

$$Q = \int g(u,t)dt \tag{2}$$

Given the quasi-steady assumption, the control variables are the engine and motor operating points. In a Pontryagin's Minimum Principle-based controller such as described in [6], the resulting Hamiltonian may then be described as

$$H(f,g,u,t) = f(u,t) + s(t)g(u,t) \tag{3}$$

In the map-based implementation utilised here, mutliple values of the Hamiltonian are obtained from the drive cycle speed and the torque required to ensure this is followed. This process involves finding the relevant engine speed for each gear to meet the drive cycle request. For each gear, the Hamiltonians are then calculated by sampling the surfaces f at a range of engine torques, and g for the remaining torque from the electrical machine required for the vehicle to follow the drive cycle. Values that result in violation of imposed constraints are disregarded and the remaining gear ratio and torque split are compared to determine the combination with the minimum Hamiltonian, which represents the optimal input combination, u^* by Pontryagin's Minimum Principle.

If the constraint set is represented by U_t, the whole process is represented by the operation:

$$u^*(t) = \arg\min_{u \in U_t} H(f,g,u,t) \tag{4}$$

Note that s is termed the *equivalence factor* as it represents the fuel-electricity equivalence, hence any approaches using a Hamiltonian of the form (3) are termed Equivalent Charge Management Strategies. If the drive cycle is known *a priori*, the optimal value $s(t) := s^*$ can be determined numerically as the constant that drives battery state of charge at the end of the cycle to a desired level.

In practice of course, the full drive cycle is unknown. However, a close-to-optimal, time varying $s(t)$ can be continually updated to enforce tracking of a given state of charge reference trajectory, q^{ref}. For non-plug in hybrids, the value of q^{ref} is a constant, as overall charge sustaining operation is sought. The scheduling of q^{ref} for PHEV operation will be dealt with in subsequent sections, but can be considered as varying with distance travelled, hence it is more appropriate to now parameterise the state of charge and Lagrange multipliers in terms of distance, x, rather than time.

It can be reasoned that the relationship from s to q implicitly has a type of integral action, and so for relatively slowly varying reference states arbitrarily close tracking may be achieved with an update law of the form:

$$s(x) = s_0 + K_p(q(x) - q^{ref}(x)) \tag{5}$$

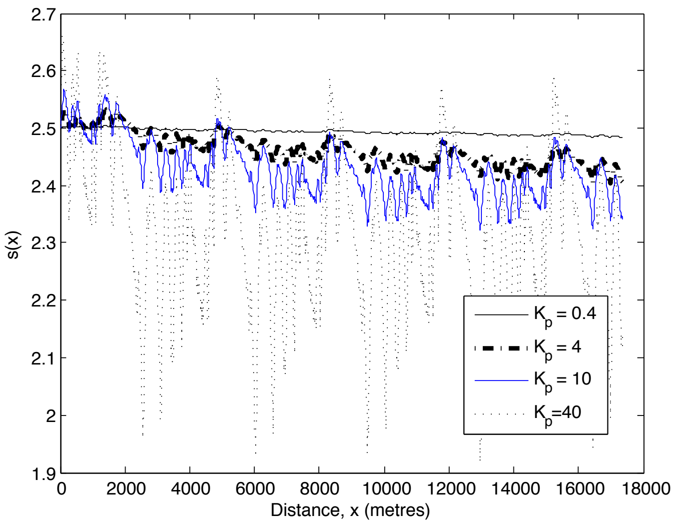

Fig. 2. Effect of gain K_p on time varying Lagrange variable

Setting the value of K_p is a tuning exercise, whereby larger values lead to faster convergence to the optimal value for the cycle, but may also cause rapid mode shifts as the ECMS controller reacts to a rapidly changing relative cost. These mode shifts can induce net fuel penalties when excess fuel is required for engine start, although these are typically unmodelled in the literature. The situation is illustrated for four different values of K_p during the modem-Hyzem base cycle in Figure 2, where the optimal value of the Lagrange multiplier may be calculated offline as $s^* = 2.375$, but the initial guess used in (5) is $s_0 = 2.5$. Based on this result, $K_p = 10$ is considered a reasonable compromise and used subsequently throughout this work.

IV. Proposed State of Charge Reference Generation

In [16], the importance of uncertainty in the fuel maps used by the Pontryagin's Minimum Principle-based hybrid controller was assessed. In this work, the uncertainty associated with vehicle operation is linked with aspects external to the vehicle and principally focussing on the journey undertaken. Note that in this work, *journey* refers to the distance travelled between grid-based recharging of the battery, and may actually constitute multiple shorter trips.

Thus while all on-board variables required by the hybrid powertrain controller (such as the fuel and electrical consumption maps, battery limits etc) are assumed accessible, only a probability density function of the total trip distance between recharging, $p_X(x_f)$, is available to schedule the state of charge reference trajectory. Of course, if more detailed trip information is known, the p.d.f. will collapse to a delta function and existing approaches may be retrieved.

However, in order to aid in the initial development of the state of charge reference trajectory, the value of x_f is assumed known and the following cost function relating to the state of charge as a function of distance, $q(x)$, is introduced:

$$J := \int_0^{x_f} \left(\frac{dq(x)}{dx} \right)^2 dx \qquad (6)$$

Note that this cost does not apply any penalty on the current value of $q(x)$, implying that there is only weak influence of battery state of charge on the overall optimal trajectory. The following Lemma is used to prescribe a trajectory for the virtual state of charge from an arbitray initial state, $q(0)$ to a desired state at the end of the journey, $q(x_f)$.

Lemma 1: If battery efficiency is sufficiently weakly dependant on battery state of charge, a locally optimal (in the context of (6)) virtual reference trajectory is:

$$q^*(x) = q(0) + \frac{x}{x_f}\left(q(x_f) - q(0)\right) \qquad (7)$$

Proof: Let $u(x) = \frac{dq(x)}{dx}$ have a small linear perturbation from constant, i.e. $u(x) = (\bar{u} - \delta) + \frac{2\delta x}{x_f}$, where $|\delta| < \bar{u}$ and $\bar{u}$ is chosen to achieve desired $q_v(x_f)$. It is readily shown that

$$\frac{dJ_q}{d\delta} = -\frac{2}{3}\delta x_f \qquad (8)$$

It follows that $\delta = 0$ minimises (6) and consequently the result of the lemma holds. ■

If the battery efficiency varies significantly with state of charge, the cost function J may be adjusted to include a state-dependant term. This leads to an optimal trajectory requiring the solution of a Riccati-like equation, and the overall problem with uncertain end distance becomes somewhat analogous to the problem described in [17]. In essence, the optimal trajectory will form a slight curve with greater durations spent in higher efficiency state of charge regions, although the ability of the controller (5) to track such a curve sufficiently closely to take advantage of any non-uniformities in battery efficiency was not observed.

A. Augmentation for uncertainties

The previous section utilised exact knowledge of the final distance in developing the reference trajectory in the absence of height and velocity considerations, which may act as sources of 'virtual' state of charge courtesy of potential and kinetic pathways. To account for these factors and incorporate the estimate of final distance, the reference trajectory (7) is now modified slightly as follows:

$$q_v(x) = q(0) + \frac{x}{\hat{x}_f}\left(q(\hat{x}_f) - q(0) + \Delta_q\right) \qquad (9)$$

The term Δ_q is added to avoid charge sustaining operation at $q = q_{min}$, as the state of charge constraint enforced on the ECMS controller leads to effectively purely ICE-mode with significantly reduced efficiency during this operation. If full drive cycle information were available, the necessary magnitude of Δ_q to just avoid encountering the battery constraint can be precisely stated in terms of the velocity and altitude, i.e.:

$$\Delta_q = q_{min} - \min_x \Big[q^{ref}(x) - \frac{\eta_{regen,p} mg}{C_{batt}}(h(x) - h(x_f)) - \frac{\eta_{regen,k}}{C_{batt}} \frac{1}{2} m v^2(x) \Big] \tag{10}$$

The penultimate and final terms in (10) represent the regeneration of potential and kinetic energy to state of charge respectively. The regenerative fractions, $\eta_{p,regen}$ and $\eta_{k,regen}$, can be approximated by constants that are determined by comparing optimal solutions obtained from offline PMP with the linear trajectories. It is also clear that the relevance of the velocity and altitude corecton decreases with increasing battery capacity, C_{batt}.

The incorporation of these influences on the state of charge trajectory may mean that without the inclusion of Δ_q, the reference may be scheduled below q_min. This invokes the state constraint on battery state of charge, and hence fuel optimality is potentially lost. The inclusion of Δ_q in (10) allows the minimum possible state of charge to be obtained by the battery without encountering the state constraint. However as in practice full drive cycle is unavailable, bounds δ_h and δ_v may be used used in the following more conservative approach:

$$\Delta_q = \frac{\eta_{regen} mg}{C_{batt}} \delta_h + \frac{\eta_{regen}}{C_{batt}} \frac{1}{2} m \delta_v^2 \tag{11}$$

In essence this represents somewhat of a trade-off, in that selecting Δ_q too low may lead to encountering the state constraint, while selecting it too high leads to incomplete utilisation of the battery. The final aspect to consider is the estimation of the final distance, $\hat{x}_f$. Using the available p.d.f. of trip duration, a conditional expectation based on the current distance travelled, x, may be used as follows:

$$\begin{aligned} \hat{x}_f(x) &= E\left(x_f | x\right) \\ &= \frac{\int_x^\infty \bar{x} p_X(\bar{x}) d\bar{x}}{\int_x^\infty p_X(\bar{x}) d\bar{x}} \end{aligned} \tag{12}$$

Note that $\hat{x}_f(x)$ is completely calculable from (12) *a priori*, leading to a reference state of charge trajectory (9) known before the journey begins. This is then used online in conjunction with the adaptive ECMS strategy (5).

V. Results

To assess the performance of the proposed approach, simulations were conducted on composite cycles with end distances stochastically determined within the cycle by a specified probability distribution. No altitude variation was augmented onto the cycles , however the existence of altitude is encompassed by using $\Delta q = 0.05$ in (9). This corresponds to an altitude difference with the altitude at the end of journey of approximately 150m - which is approximately the largest variation within the Rueil Malmaison area where IFP Energies Nouvelles is based.

To provide a benchmark, other alternative strategies were considered as described below:

- **Charge depleting-charge sustaining (CD-CS) strategy** This involves running in electric-only mode until the minimum state of charge level is reached, and then switching to a charge sustaining operation about this level.
- **Shortest journey** This assumes the shortest journey possible from $p_X(x)$ is undertaken in all journeys, and linearly schedules SoC accordingly. If the distance is surpassed, the strategy switches to charge sustaining.
- **Mean journey** This assumes the mean journey distance evaluated before the trip, $\hat{x}(0)$, is undertaken in all journeys. If the distance is surpassed, the strategy switches to charge sustaining.
- **Longest journey** This assumes the longest journey distance is undertaken in all journeys. This strategy never requires a charge sustaining mode.

The performance of each approach was measured according to both financial and environmental considerations over the weighted average of all possible end durations in each cycle. The financial assumptions used in the performance assessments are the cost of fuel and electricity are 1.4 Euro/litre and 0.2 Euro/kWh respectively. The emissions intensity of electricity is assumed to be 94.7gCO_2/MJ and 148gCO_2/MJ in Europe and the USA respectively, while gasoline is assumed to have an emissions intensity of 2.32 kg CO_2/litre.

Two types of probability distribution are now considered, with a bi-delta distribution used to illustrate the approach, and then a more representative distribution for PHEV operation.

A. Bi-delta distance probability distribution

In the first case study to demonstrate the proposed state of charge reference generator, a drive cycle composed of two iterations of the WLTP cycle, followed by two iterations of the modem-Hyzem base cycle and finished with a further iteration of the WLTP cycle is considered. The trip duration is assumed to take a bi-delta distribution, with probability p the vehicle is recharged after the first two WLTP cycles (46 km) and probability $1 - p$ the full cycle is undertaken (104km).

The different state of charge reference strategies are depicted in Figure 3, for $p = 0.2$, and encapsulate the tradeoff facing the approach. In the case of the CD-CS strategy, there will always be good utilisation of the available battery storage, but extended operation at the lower state of charge limit and the associated constrained operation by the ECMS algorithm during the charge sustaining operation has the potential to lead to fuel penalties. On the other hand, conservative use of the battery capacity will lead to higher than desirable fuel consumption in many cases.

The algorithms were run for both $p = 0.2$ and 0.8, with the cumulative performance over all drive cycles for each of the strategies relative to the proposed one contained in Table I. In keeping with known results, the CD-CS strategy is shown to be considerably worse than any of the blended strategies.

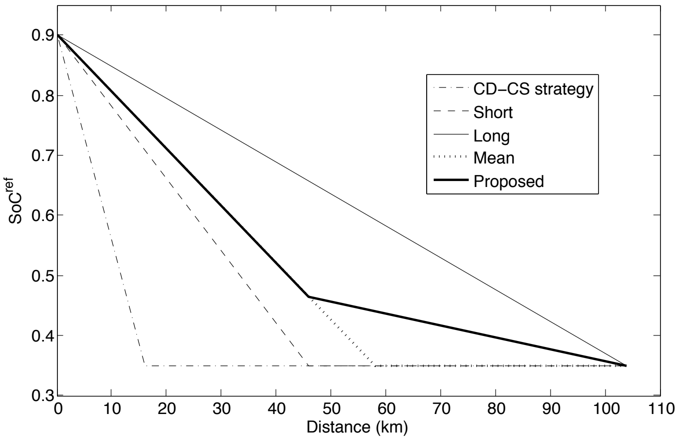

Fig. 3. Different state of charge strategies for the bi-delta probability distribution with 80% probability of travelling 46km and 20% probability of travelling 104km.

However, amongst the blended strategies the performance relative to the proposed strategy is much closer. This is attributable to several factors. Firstly, the short and long strategies will be fuel-optimal for a proportion of simulations. When not fuel-optimal, the fuel impact will depend on the drive cycle itself, the duration spent at the state of charge limit (for underestimation of journey length) and the proximity to the state of charge limit (for overestimation of journey distance). The severity of the controller constraints when operating at the state of charge limit is partially negated through the incorporation of the Δ_q variable.

TABLE I
WEIGHTED PERFORMANCE DEGRADATION OVER ALL CYCLES RELATIVE TO PROPOSED STRATEGY

	$p = 0.8$		
Strategy	Total cost	Total CO_2 (Europe)	Total CO_2 (US)
Short	0.2%	0.2%	1.1%
Mean	0.6%	0.6%	0.2 %
Long	4.0%	3.86%	1.6%
CD-CS	11.3%	11.3%	11.6%
	$p = 0.2$		
Short	1.1%	1.1%	2.1%
Mean	0.1%	0.1%	0.2%
Long	0.7%	0.8%	1.1%
CD-CS	7.6%	7.6%	8.3%

B. Pseudo-continuous probability distribution

The previous section considered a bi-delta probability distribution for the purposes of outlining the proposed strategy. However, the choice of distances is not indicative of the likely consumer usage of plug-in capability, and so a different probability distribution is now constructed. The full cycle considers the modem-Hyzem base cycle, followed by two iterations of the WLTP, a further two iterations of modem-Hyzem and then two further iterations of the WLTP. This construct allows journey terminations at 17km, 40km, 63km, 98km and 144km. Note that the first represents all journeys

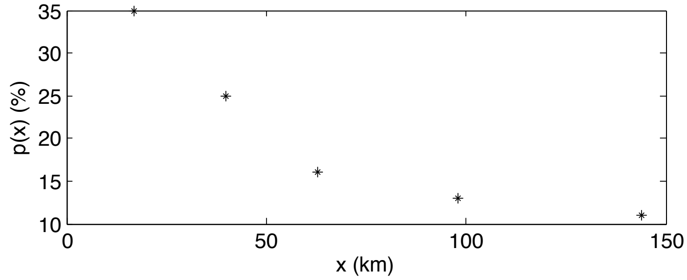

Fig. 4. Discretised probability distribution function of journeys for the cycles considered in Section V-B

in the electric range (as this vehicle has an all electric range of approximately 17km).

The probability distribution for journey duration was postulated to decay almost exponentially with distance, as illustrated in Figure 4. Here the Shortest journey and the CD-CS strategies are equivalent and so are merged together. The cumulative performance of the remaining state of charge profiles was assessed using the same metrics and indicators as in the previous section, with the results relative to the proposed strategy presented in Table II.

Under these conditions, it appears that there are relative financial and CO_2 advantages to running with either the proposed or the mean journey state of charge references. The difference between always assuming the mean journey and the proposed strategies is only very slight however. This is attributable largely to the long tail on the probability density function meaning the two strategies are relatively close, albeit with the proposed strategy always being above the state of charge limit. As was seen in the previous section, the incorporation of $\Delta_q = 0.05$ led to only a small penalty for running at the minimum state of charge, and this accounts for the small observed difference.

To quantify this effect, the mean strategy was repeated with Δ_q removed, and an increase in fuel consumption up to 3.2% was observed for the longest possible cycle. Using the cumulative performance indices relative to the proposed strategy showed that the mean strategy was 0.9% worse in terms of fuel consumption and European CO_2, and 1.5% worse in terms of US CO_2 emissions levels. This difference is solely attributable to the reduced degree of freedom available to the ECMS controller.

TABLE II
WEIGHTED PERFORMANCE DEGRADATION OVER ALL CYCLES RELATIVE TO PROPOSED STRATEGY

Strategy	Total cost	Total CO_2 (Europe)	Total CO_2 (US)
Short	2.6 %	2.8%	6.0%
Mean	0.2%	0.2 %	0.9%
Long	10.6%	10.7%	8.0 %

VI. Conclusions

A novel approach for battery state of charge scheduling for plug in hybrid electric vehicles was proposed, with the novelty arising from the removal of the standard assumption that the distance to recharge is known *a priori*. Instead the weaker assumption of a pdf of distances between recharges was made, which could be developed readily as the vehicle is used by the owner.

In combination with a map-based ECMS powertrain controller, the proposed strategy was found to offer fuel and CO_2 advantages over both charge depletion and fixed distance strategies. If a small offset, Δ_q, to the state of charge limit was incorporated in the strategy, only a negligible difference between the proposed strategy and a mean distance strategy was observed, and this was attributed to only minor penalties arising from the PMP-based ECMS controller encountering reduced degree of freedom operation at the state of charge minimum limit.

Further research opportunities exist in explicitly accounting for the engine restart and tailpipe emissions by augmenting the ECMS-cost function to include variables such as catalyst temperature and penalties on restart. Furthermore, the explicit consideration of battery efficiency and lifetime as a function of state of charge has been largely ignored in this work, although the presented framework may readily incorporate these factors.

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